# A Population-Growth Model for Multiple Generations of Technology Products

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## A Online Appendix

### A.1 Equations of Population Evolution and Competition Sales

$$
\begin{aligned}
x_i(t+1) = \;& x_i(t) + \beta_1\left[\sum_{j<i} x_j(t) - \sum_{j>i} x_i(t)\right] + \beta_2\left[\sum_{j<i} f_{ji}x_j(t) - \sum_{j>i} f_{ij}x_i(t)\right] \\
&+ \beta_3\left[\sum_{j<i} x_i(t)x_j(t) - \sum_{j>i} x_i(t)x_j(t)\right] + \beta_4\left[\sum_{j<i} f_{ji}x_i(t)x_j(t) - \sum_{j>i} f_{ij}x_i(t)x_j(t)\right] \\
&+ \beta_5\left[y(t)I(i\in J) - x_i(t)I(i\in \bar{J})\right] + \beta_6\left[f_{yi}y(t)I(i\in J) - f_{iy}x_i(t)I(i\in \bar{J})\right] \\
&+ \beta_7\left[x_i(t)y(t)(I(i\in J) - I(i\in \bar{J}))\right] + \beta_8\left[x_i(t)y(t)(f_{yi}I(i\in J) - f_{iy}I(i\in \bar{J}))\right] \\
&+ \alpha(t)s_i(t-1)\ ,
\end{aligned} \tag{A.1}
$$

$$
\begin{aligned}
y(t+1) = \;& y(t) + \beta_5\left[-\sum_{i\in J} y(t) + \sum_{i\in \bar{J}} x_i(t)\right] + \beta_6\left[-\sum_{i\in J} f_{yi}y(t) + \sum_{i\in \bar{J}} f_{iy}x_i(t)\right] \\
&+ \beta_7\left[-\sum_{i\in J} x_i(t)y(t) + \sum_{i\in \bar{J}} x_i(t)y(t)\right] + \beta_8\left[-\sum_{i\in J} f_{yi}x_i(t)y(t) + \sum_{i\in \bar{J}} f_{iy}x_i(t)y(t)\right] \\
&+ \alpha(t)s_y(t-1)\ ,
\end{aligned} \tag{A.2}
$$

$$
\begin{aligned}
s_y(t) = \;& \beta_5\left[\sum_{i\in \bar{J}} x_i(t)\right] + \beta_6\left[\sum_{i\in \bar{J}} f_{iy}x_i(t)\right] + \beta_7\left[\sum_{i\in \bar{J}} x_i(t)y(t)\right] + \beta_8\left[\sum_{i\in \bar{J}} f_{iy}x_i(t)y(t)\right] \\
&+\alpha(t)s_y(t-1)\ .
\end{aligned} \tag{A.3}
$$

### A.2 Proof of Lemma 3.2

*Proof.* For brevity we omit the argument $\boldsymbol{\beta}^k$ of $\mathbf{X}$ in the proof. Since $\mathbf{X}$ is full rank, $\mathbf{X}^T\mathbf{X}$ is invertible. Thus we can rewrite $\mathbf{d}^k$ as

$$
\begin{aligned}
\mathbf{d}^k &= (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{X}[(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{s} - \boldsymbol{\beta}^k] \\
&= (\mathbf{X}^T\mathbf{X})^{-1}(\mathbf{X}^T\mathbf{s} - \mathbf{X}^T\mathbf{X}\boldsymbol{\beta}^k) = -(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T(\mathbf{X}\boldsymbol{\beta}^k - \mathbf{s})\ .
\end{aligned}
$$

From the definition of $v(\boldsymbol{\beta})$, we have

$$\nabla v(\boldsymbol{\beta}^k) = 2[\nabla(\mathbf{X}\boldsymbol{\beta}^k)](\mathbf{X}\boldsymbol{\beta}^k - \mathbf{s})\ .$$

Thus

$$
\begin{aligned}
\frac{1}{2}[\nabla v(\boldsymbol{\beta}^k)]^T\mathbf{d}^k &= -\left\{[\nabla(\mathbf{X}\boldsymbol{\beta}^k)](\mathbf{X}\boldsymbol{\beta}^k - \mathbf{s})\right\}^T\left[(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T(\mathbf{X}\boldsymbol{\beta}^k - \mathbf{s})\right] \\
&= -(\mathbf{X}\boldsymbol{\beta}^k - \mathbf{s})^T[\nabla(\mathbf{X}\boldsymbol{\beta}^k)]^T(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T(\mathbf{X}\boldsymbol{\beta}^k - \mathbf{s}) < 0\ ,
\end{aligned}
$$

where the last inequality holds because $[\nabla(\mathbf{X}\boldsymbol{\beta}^k)]^T(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T$ is positive definite.

We have made the assumption earlier that $x_i(t)$ is always nonnegative and bounded from above. Therefore, as long as we start with a $\boldsymbol{\beta}^k$ that is bounded, $\mathbf{b}^k = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{s}$ is bounded; and thus $\beta^{k+1}$ is bounded. As a result, the sequence $\{\mathbf{d}^k\}$ is bounded and $\{\mathbf{d}^k\}$ is gradient related to $\{\boldsymbol{\beta}^k\}$. ☐

## A.3 Proof of Proposition 3.5

*Proof.* From equation (A.1), we have:

$$\begin{aligned}
\frac{\partial x_i(t+1)}{\partial \beta_1} \;=\; & \frac{\partial x_i(t)}{\partial \beta_1} + \sum_{j<i} x_j(t) - \sum_{j>i} x_j(t) + \beta_1 \frac{\partial}{\partial \beta_1}\left[\sum_{j<i} x_j(t) - \sum_{j>i} x_j(t)\right] \\
& + \beta_2 \frac{\partial}{\partial \beta_1}\left[\sum_{j<i} f_{ji}x_j(t) - \sum_{j>i} f_{ij}x_i(t)\right] + \beta_3 \frac{\partial}{\partial \beta_1}\left[\sum_{j<i} x_i(t)x_j(t) - \sum_{j>i} x_i(t)x_j(t)\right] \\
& + \beta_4 \frac{\partial}{\partial \beta_1}\left[\sum_{j<i} f_{ji}x_i(t)x_j(t) - \sum_{j>i} f_{ij}x_i(t)x_j(t)\right] + \beta_5\left[\frac{\partial y(t)}{\partial \beta_1} I(i\in J) - \frac{\partial x_i(t)}{\partial \beta_1} I(i \in \bar{J})\right] \\
& + \beta_6\left[\frac{\partial y(t)}{\partial \beta_1} f_{yi} I(i\in J) - \frac{\partial x_i(t)}{\partial \beta_1} f_{iy} I(i \in \bar{J})\right] + \beta_7 \frac{\partial x_i(t)y(t)}{\partial \beta_1}(I(i\in J) - I(i\in\bar{J}))] \\
& + \beta_8 \frac{\partial x_i(t)y(t)}{\partial \beta_1}[f_{yi}I(i\in J) - f_{iy}I(i\in \bar{J})] + \alpha(t)\frac{\partial s_i(t-1)}{\partial \beta_1}\;.
\end{aligned}$$

Since $x_i(t)$ $y(t)$, and $s_i(t)$ are bounded $\forall i, t$, it is easy to show by induction that $\frac{\partial x_i(t)}{\partial \beta_1}$, $\frac{\partial y(t)}{\partial \beta_1}$ and $\frac{\partial s_i(t)}{\partial \beta_1}$ are bounded $\forall i, t$. Since $\frac{\partial x_i(t)x_j(t)}{\partial \beta_1} = x_i(t)\frac{\partial x_j(t)}{\partial \beta_1} + x_j(t)\frac{\partial x_i(t)}{\partial \beta_1}$ and $\frac{\partial x_i(t)y(t)}{\partial \beta_1} = x_i(t)\frac{\partial y(t)}{\partial \beta_1} + y(t)\frac{\partial x_i(t)}{\partial \beta_1}$, it follows that $\frac{\partial x_i(t)x_j(t)}{\partial \beta_1}$ and $\frac{\partial x_i(t)y(t)}{\partial \beta_1}$ are also bounded. We can show similarly that $\frac{\partial x_i(t)}{\partial \beta_m}$, $\frac{\partial y(t)}{\partial \beta_m}$, $\frac{\partial s_i(t)}{\partial \beta_m}$, $\frac{\partial x_i(t)x_j(t)}{\partial \beta_m}$, and $\frac{\partial x_i(t)y(t)}{\partial \beta_m}$ where $m = 2, \ldots, 8$ are bounded. Consequently, $\lim_{\beta\to 0}(\nabla_\beta X)\beta \to 0$. Therefore,

$$\begin{aligned}
& \lim_{\beta\to 0}[\nabla(\mathbf{X}\beta)]^T(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T = \lim_{\boldsymbol{\beta}\to 0}[\mathbf{X} + (\nabla\mathbf{X})\boldsymbol{\beta}](\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T \\
= \; & \lim_{\boldsymbol{\beta}\to 0}\mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T + \lim_{\boldsymbol{\beta}\to 0}(\nabla\mathbf{X})\boldsymbol{\beta}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T = \lim_{\boldsymbol{\beta}\to 0}\mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\;,
\end{aligned}$$

where the last equality follows from $\lim_{\boldsymbol{\beta}\to 0}(\nabla_{\boldsymbol{\beta}}\mathbf{X})\boldsymbol{\beta} \to 0$. Since $\mathbf{X}$ is full rank, the term $\lim_{\boldsymbol{\beta}\to 0}\mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T$ is positive definite. (To see that $\mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T$ is positive definite, consider any $\mathbf{a} \neq 0$. Define $\mathbf{b} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{a}$; thus $\mathbf{a} = \mathbf{X}\mathbf{b}$. We then have $\mathbf{a}^T\mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{a} = \mathbf{a}^T\mathbf{X}\mathbf{b} = \mathbf{a}^T\mathbf{a} > 0$.) Hence the matrix $\lim_{\beta\to 0}[\nabla(\mathbf{X}\boldsymbol{\beta})]^T(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T$ is positive definite. From Corollary 3.3, the augmented iterative approach converges to a stationary point of $v(\boldsymbol{\beta})$. ☐

## A.4 Proof of Positive Definiteness of $(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T(\mathbf{X}\mathbf{X}^T)^{-1}\mathbf{X}$

*Proof.* To see this, consider any $\mathbf{y} \neq 0$. Define $\mathbf{b} = (\mathbf{X}\mathbf{X}^T)^{-1}\mathbf{X}\mathbf{y}$; thus $\mathbf{y} = \mathbf{X}^T\mathbf{b}$.
Therefore, $\mathbf{y}^T(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T(\mathbf{X}\mathbf{X}^T)^{-1}\mathbf{X}\mathbf{y} = \mathbf{y}^T(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{b} = \mathbf{b}^T\mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{b} > 0$, where the first equality holds by the definition of $\mathbf{b}$, the second equality holds because $\mathbf{y}^T = \mathbf{b}^T\mathbf{X}$, and the last inequality holds due to positive definiteness of $\mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T$ as shown in the proof of Proposition 3.5. ☐

## A.5 Plot of Intel's Sales

Figure 7 shows Intel's sales (data are masked).

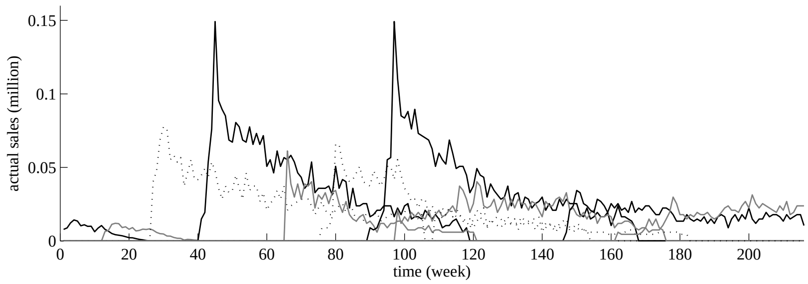


Figure 7: Intel Sales

## A.6 Additional Implementation Details of the Intel Application

In this part of the appendix, we provide additional details on the implementation of our method. The masked data set is made available with this online appendix. To ensure small $\boldsymbol{\beta}$ values, we scale down the sales by $10^6$. The trend curve estimated for total market sales (including sales by Intel and estimated sales for competition), denoted by $S(t)$, has the form $S(t) = \frac{a}{1+e^{-kt+b}}$ where $a = 0.885$, $b = 1.474$ and $k = 0.04818$, and we estimate the percentage expansion $\alpha(t)$ using $\alpha(t+1) = \frac{S(t+1)-S(t)}{S(t)}$. The iterative descent method is implemented in Matlab, using the procedure described in Section 3 and Corollary 3.3. We use the limited maximization rule (as described at the end of Section 3.2) for determining the step size. The initial parameter estimates are obtained using the cumulative sales as approximates for population path and running a linear regression as in equation (2.11). We then apply the iterative descent method to obtain the parameter estimate using the training data. This parameter estimate is then used to compute various fit and forecast errors according to the following equations. We use $\underline{t}(i)$ and $\overline{t}(i)$ to denote the introduction and ending time periods for product $i$. Let $F$ be the set of products that has sales during the training data window (the first 120 weeks), and let $F^p$ be the set of products that peaked during the training window. Let $G$ be the set of products that have sales during the test window (the 96 weeks starting from week 121) and $G^p$ be the set of products that peaked during the test window. Note that the set $F$ and set $G$ may overlap. The errors for model fit are computed as

$$
\begin{aligned}
\text{RMSE} &= \sqrt{\frac{\sum_{i\in F}\sum_{t=\underline{t}(i)}^{\overline{t}(i)}(\hat{s}_i(t)-s_i(t))^2}{\sum_{i\in F}\left(\overline{t}(i)-\underline{t}(i)+1\right)}}\ ,\\
\text{MAE} &= \frac{\sum_{i\in F}\sum_{t=\underline{t}(i)}^{\overline{t}(i)}|\hat{s}_i(t)-s_i(t)|}{\sum_{i\in F}(\overline{t}(i)-\underline{t}(i)+1)}\ ,\\
\text{MAPE} &= \frac{\sum_{i\in F}\sum_{t=\underline{t}(i)}^{\overline{t}(i)}(\hat{s}_i(t)-s_i(t))/s_i(t)}{\sum_{i\in F}(\overline{t}(i)-\underline{t}(i)+1)}\ ,\\
\text{MdMAPE} &= \text{median}\{(\hat{s}_i(t)-s_i(t))/s_i(t)\}_{i\in F,t=\underline{t}(i),\ldots,\overline{t}(i)}\ ,\\
\text{cumAPE} &= \frac{\sum_{i\in F}\sum_{t=\underline{t}(i)}^{\overline{t}(i)}(\hat{cs}_i(t)-cs_i(t))/cs_i(t)}{\sum_{i\in F}(\overline{t}(i)-\underline{t}(i)+1)}\ ,\\
\text{peakMAPE} &= \sum_{i\in F^p}(\hat{s}_i^p(t)-s_i^p(t))/s_i^p(t))/|F^p|\ ,\\
\text{timeMAE} &= \sum_{i\in F^p}(\hat{t}_i^p-t_i^p))/|F^p|\ ,
\end{aligned}
$$

where $s_i(t)$ and $\hat{s}_i(t)$ $(cs_i(t), \hat{cs}_i(t))$ represent the actual and predicted sales (cumulative sales), and $|F^p|$ denotes the size of set $F^p$. Note that if the sales of product $i \in F$ started before week 1 or ended after week 120, we revise the values of $\underline{i}(t)$ and $\overline{i}(t)$ accordingly (i.e., set $\underline{t}(i) = 1$ or $\overline{t}(i)$ to 120) when computing the fit error. Using the parameter obtained from the training data set, we generate sales forecast based on equation (2.7), as well as equations in the online appendix A.1. We do not update the parameter estimates when making forecast, so the forecasts are not based on a rolling horizon. The forecast errors are similarly computed as for the fit errors by replacing sets $F$ and $F^p$ with sets $G$ and $G^p$ respectively.

For the alternative methods, Bass, Norton-Bass and Jun-Park methods, data fitting is performed in SAS. The parameter estimates are then imported to Matlab to generate forecast and compute fit and forecast errors, following the same error measure equations shown above.

## A.7 Sensitivity to Initial Population Size

Tables 14 to 15 illustrate how the model fit, and forecast are affected when the estimate of the initial population size fluctuates. We illustrate with the "constrained, perf-only, best-comp" specification and vary the initial population of the competition, $y(0)$, and the initial population of product 1, $x_1(0)$.

| $y(0)$ | $x_1(0)$ | RMSE | MAE | MAPE | MdAPE | cum MAPE | peak MAPE | time MAE | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| $6M$ | $0M$ | 0.0175 | 0.0122 | 67% | 42% | 49% | 3.45% | 5.6 | 0.41 |
| $7M$ | $0M$ | 0.0176 | 0.0121 | 67% | 41% | 49% | 3.43% | 5.6 | 0.41 |
| $7.5M$ | $0M$ | 0.0176 | 0.0121 | 67% | 41% | 50% | 3.44% | 5.4 | 0.40 |
| $8M$ | $0M$ | 0.0177 | 0.0121 | 67% | 41% | 50% | 3.45% | 5.7 | 0.40 |
| $9M$ | $0M$ | 0.0178 | 0.0121 | 67% | 41% | 50% | 3.47% | 5.7 | 0.39 |
| $6M$ | $1M$ | 0.0175 | 0.0120 | 66% | 39% | 53% | 3.43% | 5.3 | 0.41 |
| $7M$ | $1M$ | 0.0177 | 0.0120 | 66% | 39% | 53% | 3.45% | 5.7 | 0.40 |
| $7.5M$ | $1M$ | 0.0177 | 0.0120 | 66% | 40% | 53% | 3.46% | 5.7 | 0.39 |
| $8M$ | $1M$ | 0.0178 | 0.0121 | 66% | 40% | 53% | 3.47% | 5.7 | 0.39 |
| $9M$ | $1M$ | 0.0179 | 0.0121 | 66% | 38% | 53% | 3.49% | 4.6 | 0.38 |

Table 14: Sensitivity of Model Fit to Initial Population Size

| $y(0)$ | $x_1(0)$ | RMSE | MAE | MAPE | MdAPE | cumMAPE | peakMAPE | timeMAE |
|---|---|---|---|---|---|---|---|---|
| $6M$ | $0M$ | 0.0134 | 0.0110 | 112% | 46% | 75% | 0.44% | 5.0 |
| $7M$ | $0M$ | 0.0118 | 0.0095 | 99% | 39% | 66% | 0.60% | 13.3 |
| $7.5M$ | $0M$ | 0.0111 | 0.0089 | 94% | 38% | 61% | 0.69% | 13.7 |
| $8M$ | $0M$ | 0.0105 | 0.0083 | 88% | 35% | 57% | 0.77% | 13.7 |
| $9M$ | $0M$ | 0.0095 | 0.0074 | 78% | 31% | 48% | 0.92% | 13.7 |
| $6M$ | $1M$ | 0.0118 | 0.0095 | 100% | 39% | 66% | 0.61% | 7.0 |
| $7M$ | $1M$ | 0.0105 | 0.0084 | 88% | 35% | 57% | 0.77% | 13.7 |
| $7.5M$ | $1M$ | 0.0100 | 0.0079 | 83% | 34% | 53% | 0.84% | 13.7 |
| $8M$ | $1M$ | 0.0096 | 0.0075 | 78% | 32% | 49% | 0.90% | 13.7 |
| $9M$ | $1M$ | 0.0089 | 0.0069 | 70% | 28% | 42% | 1.02% | 13.7 |

Table 15: Sensitivity of Forecast to Initial Population Size

## A.8 Product Strength as a Weighted Sum of Performance and Price

Let the gap of product strength between product $i$ and product $j$ be given by $f_{ij} = g_{ij} + wr_{ij}$, where $g_{ij}$ represents performance improvement and $r_{ij}$ represents the price improvement from product $i$ to product $j$. Therefore, the "perf-only" specification, in which $f_{ij} = g_{ij}$, is a special case with weight $w = 0$. Tables 16 and 17 show the fit and forecast performance respectively as the weight $w$ increases.

| $w$ | RMSE | MAE | MAPE |
|---|---|---|---|
| 0.00 | 0.017607 | 0.01210 | 66.7% |
| 0.01 | 0.017607 | 0.01210 | 66.7% |
| 0.05 | 0.017612 | 0.01212 | 66.9% |
| 0.10 | 0.017625 | 0.01215 | 67.2% |
| 0.20 | 0.017666 | 0.01223 | 67.8% |
| 0.30 | 0.017719 | 0.01232 | 68.3% |
| 0.40 | 0.017773 | 0.01240 | 68.6% |
| 0.50 | 0.017809 | 0.01241 | 68.6% |

Table 16: Model Fit as the Weight of Price Increases ("constrained, best-comp")

| $w$ | RMSE | MAE | MAPE |
|---|---|---|---|
| 0.00 | 0.0111 | 0.0089 | 94% |
| 0.01 | 0.0112 | 0.0090 | 94% |
| 0.05 | 0.0115 | 0.0093 | 98% |
| 0.10 | 0.0119 | 0.0097 | 101% |
| 0.20 | 0.0127 | 0.0104 | 108% |
| 0.30 | 0.0135 | 0.0112 | 115% |
| 0.40 | 0.0146 | 0.0122 | 124% |
| 0.50 | 0.0155 | 0.0131 | 130% |

Table 17: Forecast Performance as the Weight of Price Increases ("constrained, best-comp")

**INTEL SALES**

| Week | Product 1 | Product 2 | Product 3 | Product 4 | Product 5 | Product 6 | Product 7 | Product 8 | Product 9 | Product 10 | Product 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 7825 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 8806 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 12192 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 14242 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 13506 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 10300 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 10960 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 9941 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 9996 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 6235 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 11 | 8686 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 12 | 10415 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 13 | 7866 | 6360 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 14 | 6584 | 7077 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 15 | 4985 | 11268 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 16 | 4215 | 11965 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 17 | 3889 | 11723 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 18 | 3479 | 9041 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 19 | 2845 | 9603 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 20 | 2184 | 7886 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 21 | 2067 | 9091 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 22 | 1546 | 6736 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 23 | 1031 | 7176 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 24 | 735 | 7972 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 25 | 238 | 7764 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 26 | 56 | 8205 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 27 | 0 | 7275 | 40284 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 28 | 0 | 5813 | 47744 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 29 | 0 | 4938 | 68632 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 30 | 0 | 4701 | 77584 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 31 | 0 | 3316 | 76092 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 32 | 0 | 3273 | 55204 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 33 | 0 | 2348 | 58188 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 34 | 0 | 1817 | 53712 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 35 | 0 | 1692 | 56696 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 36 | 0 | 558 | 37300 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 37 | 0 | 1045 | 46252 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 38 | 0 | 842 | 55204 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 39 | 0 | 597 | 41776 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 40 | 0 | 415 | 41776 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 41 | 0 | 0 | 44760 | 14920 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 42 | 0 | 0 | 49236 | 19396 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 43 | 0 | 0 | 43268 | 53712 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 44 | 0 | 0 | 53712 | 76092 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 45 | 0 | 0 | 47744 | 149200 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 46 | 0 | 0 | 35808 | 95488 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 47 | 0 | 0 | 28348 | 89520 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 48 | 0 | 0 | 37300 | 85044 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 49 | 0 | 0 | 32824 | 68632 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 50 | 0 | 0 | 34316 | 67140 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 51 | 0 | 0 | 44760 | 80568 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 52 | 0 | 0 | 35808 | 77584 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 53 | 0 | 0 | 28348 | 68632 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 54 | 0 | 0 | 46252 | 67140 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 55 | 0 | 0 | 34316 | 77584 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 56 | 0 | 0 | 37300 | 65648 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 57 | 0 | 0 | 37300 | 73108 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 58 | 0 | 0 | 26856 | 65648 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 59 | 0 | 0 | 32824 | 71616 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 60 | 0 | 0 | 20888 | 50728 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 61 | 0 | 0 | 25364 | 55204 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 62 | 0 | 0 | 28348 | 46252 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 63 | 0 | 0 | 34316 | 61172 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 64 | 0 | 0 | 28348 | 50728 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 65 | 0 | 0 | 37300 | 56696 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 66 | 0 | 0 | 20888 | 55204 | 61172 | 0 | 0 | 0 | 0 | 0 | 0 |
| 67 | 0 | 0 | 23872 | 58188 | 38792 | 0 | 0 | 0 | 0 | 0 | 0 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 68 | 0 | 0 | 25364 | 53712 | 29840 | 0 | 0 | 0 | 0 | 0 | 0 |
| 69 | 0 | 0 | 26856 | 46252 | 38792 | 0 | 0 | 0 | 0 | 0 | 0 |
| 70 | 0 | 0 | 28348 | 43268 | 28348 | 0 | 0 | 0 | 0 | 0 | 0 |
| 71 | 0 | 0 | 28348 | 35808 | 38792 | 0 | 0 | 0 | 0 | 0 | 0 |
| 72 | 0 | 0 | 28348 | 38792 | 37300 | 0 | 0 | 0 | 0 | 0 | 0 |
| 73 | 0 | 0 | 23872 | 53712 | 40284 | 0 | 0 | 0 | 0 | 0 | 0 |
| 74 | 0 | 0 | 17904 | 32824 | 22380 | 0 | 0 | 0 | 0 | 0 | 0 |
| 75 | 0 | 0 | 22380 | 35808 | 31332 | 0 | 0 | 0 | 0 | 0 | 0 |
| 76 | 0 | 0 | 26856 | 35808 | 28348 | 8952 | 0 | 0 | 0 | 0 | 0 |
| 77 | 0 | 0 | 20888 | 35808 | 32824 | 8952 | 0 | 0 | 0 | 0 | 0 |
| 78 | 0 | 0 | 17904 | 37300 | 25364 | 8952 | 0 | 0 | 0 | 0 | 0 |
| 79 | 0 | 0 | 17904 | 31332 | 32824 | 16412 | 0 | 0 | 0 | 0 | 0 |
| 80 | 0 | 0 | 20888 | 50728 | 34316 | 65648 | 0 | 0 | 0 | 0 | 0 |
| 81 | 0 | 0 | 23872 | 35808 | 25364 | 65648 | 0 | 0 | 0 | 0 | 0 |
| 82 | 0 | 0 | 25364 | 41776 | 19396 | 52220 | 0 | 0 | 0 | 0 | 0 |
| 83 | 0 | 0 | 19396 | 40284 | 26856 | 44760 | 0 | 0 | 0 | 0 | 0 |
| 84 | 0 | 0 | 25364 | 22380 | 17904 | 40284 | 0 | 0 | 0 | 0 | 0 |
| 85 | 0 | 0 | 20888 | 35808 | 14920 | 41776 | 0 | 0 | 0 | 0 | 0 |
| 86 | 0 | 0 | 13428 | 23872 | 13428 | 46252 | 0 | 0 | 0 | 0 | 0 |
| 87 | 0 | 0 | 16412 | 23872 | 16412 | 50728 | 0 | 0 | 0 | 0 | 0 |
| 88 | 0 | 0 | 13428 | 25364 | 17904 | 40284 | 0 | 0 | 0 | 0 | 0 |
| 89 | 0 | 0 | 19396 | 25364 | 11936 | 38792 | 0 | 0 | 0 | 0 | 0 |
| 90 | 0 | 0 | 17904 | 16412 | 13428 | 37300 | 8952 | 0 | 0 | 0 | 0 |
| 91 | 0 | 0 | 17904 | 17904 | 10444 | 47744 | 7460 | 0 | 0 | 0 | 0 |
| 92 | 0 | 0 | 19396 | 20888 | 5968 | 43268 | 8952 | 0 | 0 | 0 | 0 |
| 93 | 0 | 0 | 13428 | 20888 | 11936 | 37300 | 14920 | 0 | 0 | 0 | 0 |
| 94 | 0 | 0 | 14920 | 23872 | 11936 | 41776 | 20888 | 0 | 0 | 0 | 0 |
| 95 | 0 | 0 | 16412 | 23872 | 8952 | 50728 | 55204 | 0 | 0 | 0 | 0 |
| 96 | 0 | 0 | 17904 | 23872 | 11936 | 50728 | 56696 | 0 | 0 | 0 | 0 |
| 97 | 0 | 0 | 19396 | 16412 | 11936 | 41776 | 149200 | 0 | 0 | 0 | 0 |
| 98 | 0 | 0 | 20888 | 22380 | 13428 | 55204 | 110408 | 20888 | 0 | 0 | 0 |
| 99 | 0 | 0 | 17904 | 17904 | 13428 | 44760 | 85044 | 11936 | 0 | 0 | 0 |
| 100 | 0 | 0 | 19396 | 23872 | 10444 | 35808 | 83552 | 16412 | 0 | 0 | 0 |
| 101 | 0 | 0 | 23872 | 25364 | 7460 | 32824 | 88028 | 13428 | 0 | 0 | 0 |
| 102 | 0 | 0 | 17904 | 14920 | 7460 | 26856 | 76092 | 19396 | 0 | 0 | 0 |
| 103 | 0 | 0 | 17904 | 16412 | 7460 | 28348 | 89520 | 16412 | 0 | 0 | 0 |
| 104 | 0 | 0 | 14920 | 16412 | 8952 | 22380 | 73108 | 19396 | 0 | 0 | 0 |
| 105 | 0 | 0 | 17904 | 14920 | 8952 | 28348 | 71616 | 16412 | 0 | 0 | 0 |
| 106 | 0 | 0 | 0 | 20888 | 7460 | 28348 | 70124 | 14920 | 0 | 0 | 0 |
| 107 | 0 | 0 | 0 | 17904 | 10444 | 17904 | 68632 | 20888 | 0 | 0 | 0 |
| 108 | 0 | 0 | 0 | 14920 | 5968 | 23872 | 62664 | 13428 | 0 | 0 | 0 |
| 109 | 0 | 0 | 0 | 17904 | 7460 | 19396 | 50728 | 17904 | 17904 | 0 | 0 |
| 110 | 0 | 0 | 0 | 14920 | 7460 | 20888 | 59680 | 20888 | 14920 | 0 | 0 |
| 111 | 0 | 0 | 0 | 8952 | 5968 | 14920 | 55204 | 16412 | 22380 | 0 | 0 |
| 112 | 0 | 0 | 0 | 10444 | 5968 | 17904 | 52220 | 17904 | 17904 | 0 | 0 |
| 113 | 0 | 0 | 0 | 10444 | 5968 | 22380 | 68632 | 20888 | 22380 | 0 | 0 |
| 114 | 0 | 0 | 0 | 13428 | 5968 | 16412 | 59680 | 23872 | 19396 | 0 | 0 |
| 115 | 0 | 0 | 0 | 14920 | 5968 | 22380 | 49236 | 19396 | 16412 | 0 | 0 |
| 116 | 0 | 0 | 0 | 10444 | 5968 | 17904 | 50728 | 37300 | 17904 | 0 | 0 |
| 117 | 0 | 0 | 0 | 5968 | 5968 | 13428 | 50728 | 34316 | 14920 | 0 | 0 |
| 118 | 0 | 0 | 0 | 8952 | 7460 | 13428 | 44760 | 28348 | 13428 | 0 | 0 |
| 119 | 0 | 0 | 0 | 0 | 5968 | 8952 | 32824 | 19396 | 14920 | 0 | 0 |
| 120 | 0 | 0 | 0 | 0 | 5968 | 14920 | 37300 | 25364 | 8952 | 0 | 0 |
| 121 | 0 | 0 | 0 | 0 | 0 | 20888 | 49236 | 40284 | 13428 | 0 | 0 |
| 122 | 0 | 0 | 0 | 0 | 0 | 17904 | 44760 | 37300 | 16412 | 0 | 0 |
| 123 | 0 | 0 | 0 | 0 | 0 | 22380 | 43268 | 23872 | 11936 | 0 | 0 |
| 124 | 0 | 0 | 0 | 0 | 0 | 10444 | 29840 | 22380 | 8952 | 0 | 0 |
| 125 | 0 | 0 | 0 | 0 | 0 | 11936 | 38792 | 23872 | 14920 | 0 | 0 |
| 126 | 0 | 0 | 0 | 0 | 0 | 14920 | 34316 | 28348 | 11936 | 0 | 0 |
| 127 | 0 | 0 | 0 | 0 | 0 | 16412 | 31332 | 19396 | 10444 | 0 | 0 |
| 128 | 0 | 0 | 0 | 0 | 0 | 14920 | 28348 | 23872 | 8952 | 0 | 0 |
| 129 | 0 | 0 | 0 | 0 | 0 | 11936 | 29840 | 29840 | 13428 | 0 | 0 |
| 130 | 0 | 0 | 0 | 0 | 0 | 10444 | 37300 | 20888 | 16412 | 0 | 0 |
| 131 | 0 | 0 | 0 | 0 | 0 | 11936 | 23872 | 28348 | 11936 | 0 | 0 |
| 132 | 0 | 0 | 0 | 0 | 0 | 11936 | 31332 | 22380 | 14920 | 0 | 0 |
| 133 | 0 | 0 | 0 | 0 | 0 | 11936 | 32824 | 28348 | 7460 | 0 | 0 |
| 134 | 0 | 0 | 0 | 0 | 0 | 16412 | 22380 | 25364 | 13428 | 0 | 0 |
| 135 | 0 | 0 | 0 | 0 | 0 | 13428 | 29840 | 25364 | 10444 | 0 | 0 |
| 136 | 0 | 0 | 0 | 0 | 0 | 13428 | 28348 | 20888 | 11936 | 0 | 0 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 137 | 0 | 0 | 0 | 0 | 0 | 14920 | 22380 | 26856 | 13428 | 0 | 0 |
| 138 | 0 | 0 | 0 | 0 | 0 | 14920 | 25364 | 25364 | 7460 | 0 | 0 |
| 139 | 0 | 0 | 0 | 0 | 0 | 16412 | 26856 | 20888 | 11936 | 0 | 0 |
| 140 | 0 | 0 | 0 | 0 | 0 | 5968 | 29840 | 16412 | 11936 | 0 | 0 |
| 141 | 0 | 0 | 0 | 0 | 0 | 11936 | 20888 | 26856 | 8952 | 0 | 0 |
| 142 | 0 | 0 | 0 | 0 | 0 | 11936 | 25364 | 23872 | 11936 | 0 | 0 |
| 143 | 0 | 0 | 0 | 0 | 0 | 8952 | 20888 | 23872 | 8952 | 0 | 0 |
| 144 | 0 | 0 | 0 | 0 | 0 | 10444 | 20888 | 28348 | 5968 | 0 | 0 |
| 145 | 0 | 0 | 0 | 0 | 0 | 8952 | 28348 | 29840 | 11936 | 0 | 0 |
| 146 | 0 | 0 | 0 | 0 | 0 | 10444 | 23872 | 26856 | 13428 | 0 | 0 |
| 147 | 0 | 0 | 0 | 0 | 0 | 10444 | 28348 | 32824 | 14920 | 5968 | 0 |
| 148 | 0 | 0 | 0 | 0 | 0 | 7460 | 25364 | 20888 | 8952 | 20888 | 0 |
| 149 | 0 | 0 | 0 | 0 | 0 | 5968 | 25364 | 22380 | 8952 | 23872 | 0 |
| 150 | 0 | 0 | 0 | 0 | 0 | 8952 | 25364 | 17904 | 11936 | 34316 | 0 |
| 151 | 0 | 0 | 0 | 0 | 0 | 7460 | 17904 | 16412 | 10444 | 32824 | 0 |
| 152 | 0 | 0 | 0 | 0 | 0 | 7460 | 16412 | 19396 | 5968 | 25364 | 0 |
| 153 | 0 | 0 | 0 | 0 | 0 | 7460 | 22380 | 14920 | 7460 | 23872 | 0 |
| 154 | 0 | 0 | 0 | 0 | 0 | 0 | 14920 | 19396 | 5968 | 20888 | 0 |
| 155 | 0 | 0 | 0 | 0 | 0 | 0 | 16412 | 20888 | 5968 | 19396 | 0 |
| 156 | 0 | 0 | 0 | 0 | 0 | 0 | 19396 | 11936 | 5968 | 28348 | 0 |
| 157 | 0 | 0 | 0 | 0 | 0 | 0 | 16412 | 16412 | 5968 | 26856 | 0 |
| 158 | 0 | 0 | 0 | 0 | 0 | 0 | 16412 | 16412 | 5968 | 23872 | 0 |
| 159 | 0 | 0 | 0 | 0 | 0 | 0 | 19396 | 17904 | 4476 | 19396 | 0 |
| 160 | 0 | 0 | 0 | 0 | 0 | 0 | 10444 | 16412 | 4476 | 25364 | 0 |
| 161 | 0 | 0 | 0 | 0 | 0 | 0 | 16412 | 8952 | 4476 | 22380 | 0 |
| 162 | 0 | 0 | 0 | 0 | 0 | 0 | 23872 | 11936 | 5968 | 25364 | 5968 |
| 163 | 0 | 0 | 0 | 0 | 0 | 0 | 16412 | 11936 | 4476 | 20888 | 4476 |
| 164 | 0 | 0 | 0 | 0 | 0 | 0 | 16412 | 13428 | 5968 | 22380 | 4476 |
| 165 | 0 | 0 | 0 | 0 | 0 | 0 | 14920 | 13428 | 7460 | 19396 | 4476 |
| 166 | 0 | 0 | 0 | 0 | 0 | 0 | 13428 | 11936 | 7460 | 26856 | 4476 |
| 167 | 0 | 0 | 0 | 0 | 0 | 0 | 8952 | 8952 | 4476 | 19396 | 4476 |
| 168 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7460 | 4476 | 22380 | 4476 |
| 169 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 8952 | 4476 | 20888 | 5968 |
| 170 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 8952 | 4476 | 23872 | 8952 |
| 171 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14920 | 4476 | 23872 | 5968 |
| 172 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10444 | 4476 | 20888 | 7460 |
| 173 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14920 | 4476 | 17904 | 7460 |
| 174 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 8952 | 5968 | 17904 | 7460 |
| 175 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7460 | 5968 | 22380 | 10444 |
| 176 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 5968 | 22380 | 14920 |
| 177 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 5968 | 20888 | 19396 |
| 178 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 5968 | 17904 | 29840 |
| 179 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 5968 | 13428 | 25364 |
| 180 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 4476 | 13428 | 17904 |
| 181 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 4476 | 13428 | 17904 |
| 182 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 4476 | 17904 | 14920 |
| 183 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14920 | 17904 |
| 184 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 13428 | 16412 |
| 185 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14920 | 19396 |
| 186 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 13428 | 17904 |
| 187 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 16412 | 17904 |
| 188 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 11936 | 19396 |
| 189 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14920 | 16412 |
| 190 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 11936 | 14920 |
| 191 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 16412 | 16412 |
| 192 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 17904 | 19396 |
| 193 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 16412 | 22380 |
| 194 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 8952 | 23872 |
| 195 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14920 | 20888 |
| 196 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 17904 | 20888 |
| 197 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 13428 | 19396 |
| 198 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 17904 | 23872 |
| 199 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14920 | 26856 |
| 200 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22380 | 22380 |
| 201 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14920 | 31332 |
| 202 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 11936 | 25364 |
| 203 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14920 | 22380 |
| 204 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14920 | 25364 |
| 205 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 19396 | 23872 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 206 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 16412 | 22380 |
| 207 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 17904 | 20888 |
| 208 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 17904 | 19396 |
| 209 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 16412 | 23872 |
| 210 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 13428 | 20888 |
| 211 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 17904 | 26856 |
| 212 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14920 | 17904 |
| 213 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 16412 | 19396 |
| 214 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 17904 | 23872 |
| 215 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 17904 | 23872 |
| 216 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10444 | 23872 |

**INTEL PRICE AND PERFORMANCE**

| Product | Price | Performance |
|---|---|---|
| 1 | $ 999 | 14.0 |
| 2 | $ 999 | 16.4 |
| 3 | $ 999 | 22.7 |
| 4 | $ 999 | 25.0 |
| 5 | $ 1,199 | 27.4 |
| 6 | $ 999 | 31.3 |
| 7 | $ 999 | 33.0 |
| 8 | $ 999 | 41.6 |
| 9 | $ 1,399 | 47.0 |
| 10 | $ 1,499 | 55.2 |
| 11 | $ 999 | 57.2 |

**COMPETITION PRICE AND PERFORMANCE**

| Competition | Price | Performance |
|---|---|---|
| weeks 1-19 | $ 1,031 | 15.5 |
| weeks 20-47 | $ 1,031 | 17.0 |
| weeks 48-64 | $ 999 | 19.0 |
| weeks 65-83 | $ 459 | 20.0 |
| weeks 84-97 | $ 239 | 21.0 |
| weeks 98-114 | $ 275 | 22.3 |
| weeks 115-127 | $ 235 | 24.2 |
| weeks 128-149 | $ 235 | 24.7 |
| weeks 150-165 | $ 275 | 28.7 |
| weeks 166-181 | $ 195 | 29.8 |
| weeks 182-216 | $ 195 | 31.7 |